Research Article

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Yield and vegetation index of different maize varieties and nitrogen doses under normal irrigation

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Abstract: Nitrogen is essential nutrient that supports the growth and yield of corn. The correct dose of nitrogen fertilization is one of the keys to increasing corn productivity by its yield potential. Using unmanned aerial vehicle (UAV) drones, the normalized difference vegetation index (NDVI) can be obtained, which can provide accurate information about the health condition of plant vegetation directly. Therefore, this study aimed to determine the effect of nitrogen fertilizer dose and type of maize variety on crop production and vegetation index obtained through UAV technology. This study was designed with a separate plot design and a group randomized design as the environmental design. The research was conducted by applying various doses of nitrogen (0, 50, 100, 150, 200, and 250) and maize varieties (Sinhas, Nasa 29, HJ 36, Bisi 18, and Pioneer). The combination of all treatments resulted in 35 combinations and was repeated three times, resulting in 105 experimental units. Vegetation condition measurements were conducted using drones at time intervals (40, 55, and 70 DAP). Selection criteria were determined systematically through Pearson correlation, path, and principal component analysis (PCA). The results showed that higher nitrogen doses increased NDVI values, which reflected better vegetation health and contributed to increased crop yields. The PCA results showed that four principal components had eigenvalues greater than 1 with a cumulative proportion of 0.21. This research indicates that using optimal nitrogen doses and vegetation health monitoring using UAVs can significantly increase maize yields. These findings provide valuable insights to increase maize production through the best maize cultivation technologies that farmers can use.

Keywords: nitrogen, Zea maize, normalized difference vegetation index, PCA, yield

1 Introduction

Maize (*Zea mays* L.) is a carbohydrate-producing food crop for most of the world's population that is widely used as an industrial fuel, food source, feed, and bioethanol production [1,2]. Maize development on a broader scale with higher production can improve the regional economy. National maize productivity in 2020 and 2021 was only around 5.22 and 5.24 $t \cdot ha^{-1}$, respectively, or only increased by around 0.20%. This productivity is still relatively low compared to the genetic production potential based on variety descriptions (10–12 $t \cdot ha^{-1}$) [3]. This condition is because the released hybrid varieties were selected under optimal conditions; meanwhile, the corn development land is marginal mainly due to land conversion and global climate change. This causes maize extension programs directed at marginal lands such as dry-humid lands. Global warming causes changes in environmental balance, such as temperature intensity and rainfall, so most lands change their status to suboptimal [4,5]. Global warming also reduces soil function and characteristics, so the soil does not optimally support the plant growth [6]. Plant growth and environmental management are two things that can improve and increase land productivity. The action or activity of managing the growing environment can be done through plant fertilization.

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Fertilization is an effort to add or engineer nutrients to make them available to plants. It is essential in supporting plant growth and production [7,8]. In general, fertilization in maize has developed a lot based on the type, dosage, and application. Nitrogen fertilizers are macro-fertilizers and are essential in maize growth and productivity. Nitrogen fertilizers play a significant role in forming proteins and enzymes, including chlorophyll [8–10]. High nitrogen levels will result in ineffective photosynthesis, susceptibility to plant-disrupting organisms, drought, and reduced product quality [11]. Therefore, the correct dose of nitrogen fertilization is one of the keys to increasing corn productivity by its yield potential.

The effectiveness of nitrogen fertilization can be optimized through unmanned aerial vehicle (UAV) drone imaging, an uncrewed aircraft driven by a remote control from a distance. Using UAV drones in agriculture can help monitor crop conditions, maintain crops, and predict crop growth and productivity [12–14]. According to studies of Miller et al. and Sakinah et al. [15,16], monitoring plant growth can be done using the normalized difference vegetation index (NDVI) method, where data images were acquired using near-infrared (NIR) or RBG cameras. The UAVs are equipped with tools in the form of multispectral cameras that support agricultural activities in monitoring plant development. This camera can provide various types of information such as the number of plants, nitrogen nutrient status, and health level through the greenness value of plants using the NDVI [12,17]. Living green plants absorb solar radiation in the process of photosynthesis. Chlorophyll in plants will emit more solar radiation to the NIR camera, so plants with average growth will appear greener when compared to plants that have abnormal growth [18].

Several researchers with various systems have developed the drone-based vegetation index for nitrogen fertilization of corn [9,19,20]. However, the research studies were conducted in a subtropical climate with relatively uniform agroecosystems, cultures, and monocultures. This condition is very different from Indonesia because Indonesia has a tropical climate with very diverse agroecosystems and cultures [21,22]. This indicates that Indonesia's developed vegetation index cannot be applied optimally. Therefore, a vegetation index model for nitrogen fertilization of corn crops in Indonesia still needs to be developed. This research aims to produce a vegetation index model for nitrogen fertilization in estimating corn productivity and compare the accuracy of the vegetation index of corn plants to that of nitrogen.

2 Materials and methods

This research was conducted at the Experimental Station of the Cereal Crops Research Center (KP) Bajeng, Bajeng District, Gowa Regency, South Sulawesi, at an altitude of 27.2 m above the sea level, with coordinates 5o18'21.5″ N, 119o28'38.6″ E. The research was carried out in February to May 2023.

2.1 Experimental design

This phase focused on the effect of a combination of nitrogen doses on the growth response of several corn varieties. This study was designed with a split-plot design and a randomized group design as the environmental design. By dividing the experiment into similar blocks and using random allocation of treatments within those blocks, this design minimizes environmental variability that could affect the results of the experiment. The main plot was nitrogen dosage consisting of seven dosage levels (N0: 0 kg/ha, N1: 50 kg/ha, N2: 100 kg/ha, N3: 150 kg/ha, N4: 200 kg/ha, N5: 250 kg/ha, and N6: 300 kg/ha). The subplots are corn varieties consisting of five levels, which are V1: Sinhas, V2: Nasa 29, V3: HJ 36, V4: Bisi 18, and V5: Pioneer. The combination of all treatments resulted in 35 combinations and was repeated thrice, resulting in 105 experimental units.

2.2 Research procedure

Land preparation started with clearing the land of weeds and then plowing. The land was then made into three blocks with a size of 3 m × 5 m and a distance of 100 cm between blocks. Two seeds were planted in each planting hole with a 75 cm × 20 cm spacing. After 2 weeks, thinning and replanting were done in each planting hole so that each hole contained only one plant.

Maintenance activities carried out in this study included fertilization, irrigation at 7-day intervals, weeding, hilling, pest and disease control, and insect control. Fertilization was done three times using urea, SP36, and Phonska fertilizers at the age of 7 DAP, 35 DAP, and 50 DAP. Watering was done every 10 days until harvest, depending on weather conditions. Weeding was done when the plants were 10 DAP and 35 DAP by clearing weeds around the corn plants. Hilling was done when the plants were 35 DAP by raising the mounds and loosening the soil. Pest and disease control was done by spraying pesticides. Harvesting was done when the cobs reached physiological maturity (black spots at the base of the seeds) or around 100 DAP.

2.3 Observations

The parameters observed were plant height, number of leaves, stem diameter, cob height, male flowering age, female flowering age, panicle exit interval, harvest age, chlorophyll a, chlorophyll b, total chlorophyll, SPAD (Soil Plant Analysis Development) chlorophyll meter, cob weight, cob diameter, cob length, seeded cob length, number of seeds per row, 100 seed weight, yield percentage, and yield. The concept of these parameters has been reported by Abduh et al. [23] and Fikri et al. [24]. Meanwhile, leaf pigment parameters included total chlorophyll based on the chlorophyll content meter (CCM), NDVI, green seeker, and NDVI-UAV. Chlorophyll observations based on CCM 200+, SPAD, were carried out on the third leaf from the top of the plant, the middle leaf, and the lowest leaf at 60 DAP. The chlorophyll index was calculated using the formula: chlorophyll index = average leaf chlorophyll index + standard deviation. The procedure and concept analysis of CCM 200+ was adopted from the studies of Rakutko et al. [25], Almansoori et al. [26], and Ardiansyah et al. [10], which have been adjusted to the research conditions. The NDVI-UAV value can be used for crop analysis of corn seed production as a different application than NDVI Greenseeker (ground-based platform). UAV images in data collection were taken in three stages of plant age, namely 40, 55, and 70 DAP. The selection of 40, 55, and 70 DAP intervals for NDVI measurements was scientifically based on the need to capture key changes in plant physiology during different growth phases. At each point, plants underwent significant changes in biomass, leaf number, and photosynthetic activity, directly reflected in fluctuations in NDVI values. This NDVI-UAV captured the plant condition with a plot image on an aerial platform (Figure 1). Meanwhile, the NDVI calculation was performed using the following equation:

$$\mathrm{NDVI} = \frac{\mathrm{IMD} - M}{\mathrm{IMD} + M},$$

where M represents red and IMD represents NIR.

The procedure and concept analysis of NDVI-UAV was adopted from the studies of Singhal et al. [27], Padjung et al. [14], and Miller et al. [15], which have been adjusted to the research conditions.

2.4 Data analysis

The data obtained were analyzed using analysis of variance (ANOVA) and a split-plot design. ANOVA results became the basis for determining the heritability of characters in a broad sense where the classification of heritability is divided into three, namely high (>50%), medium (20–50%), and low (<20%). In addition to heritability in a broad sense, the determination of the genotype coefficient of variation (GCV) was also analyzed with the following formula:

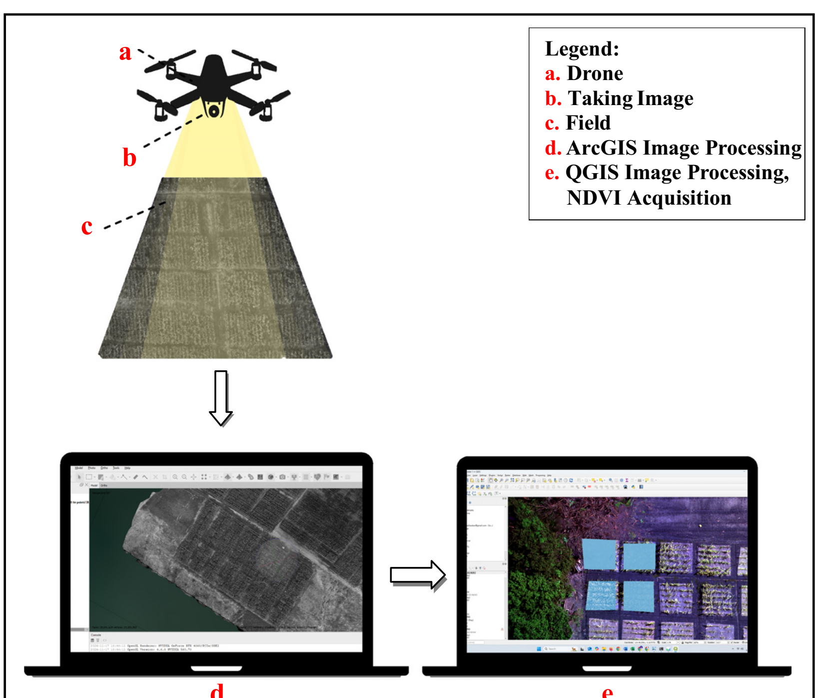

Figure 1: Drone image acquisition, data processing with ArcGIS, and NDVI analysis in QGIS.

$$\mathrm{GCV} = \frac{\sqrt{\sigma g}}{X} \times 100\%,$$

where σg represents the genetic variance and X represents the population mean.

GCV criteria also consist of three components, namely very high (>14.5%), medium (5–14.5%), and narrow (0–5%) [28]. Selection criteria were determined systematically through Pearson correlation, path, and principal component analysis (PCA) [29,30]. In addition, the analysis also continued with the development of cropping models by utilizing drone analysis, physiology, and agronomy.

3 Results

3.1 ANOVA

ANOVA showed that all characters related to growth, physiology, and yield of corn were significantly affected by nitrogen, variety, and interaction between nitrogen and variety (Table 1). The results of heritability values are listed in Table 1. From the table, traits related to growth, physiology, and yield showed high heritability values, namely the number of leaves (51.73), male flowering age (93.62), female flowering age (90.58), harvest age (89.89), chlorophyll (82.21), cob location (75.64), cob diameter (75.54), and yield percentage (55.90). The characters with moderate heritability values were plant height (42.84), SPAD (45.75), cob weight (27.26), number of seed rows (45.54), 1000 seed weight (42.66), and yield (49.06). However, characters with low heritability values were stem diameter (6.72), anthesis-silking interval (1.60), NDVI.1 (23.03), NDVI.2 (5.79), NDVI.3 (12.72), cob length (15.00), and seed cob length (13.79). Furthermore, the average coefficient of variation (CV) for most of the parameters studied ranged from 1.28% to 13.39%, as detailed in Table 1. The CV is also often used by plant breeders as one of the alternatives in the selection process, which gives an idea of diversity in a population.

3.2 NDVI-UAV

ANOVA of NDVI-UAV showed that the interaction between nitrogen dosage and corn varieties had a significant effect.

Table 1: ANOVA of maize growth characters in complete diallel hierarchical populations

Character	N	V	N × V	CV (n) (%)	CV (v) (%)	RG	RF	RL	H2 (%)
PH	92.357**	257.239**	121.088**	1.26	1.58	6.48	15.13	8.65	42.84
NL	24.872**	0.907*	0.406	3.19	2.85	0.02	0.36	0.33	6.72
SD	5.908**	6.012**	0.675**	4.21	3.85	0.25	0.49	0.24	51.73
MFA	57.149**	259.595**	10.701**	2.16	1.65	11.85	12.66	0.81	93.62
FFA	79.771**	247.919**	10.958**	2.35	1.85	11.28	12.46	1.17	90.58
ASI	18.133**	2.343	11.390	14.07	13.39	0.01	0.33	0.33	1.60
HA	520.914**	1004.724**	285.943**	1.72	1.28	11.39	12.67	1.28	89.89
CH	245.925	3854.855**	3413.840**	4.28	3.73	39.12	51.71	12.60	75.64
CW	3988.660**	1014.818**	4958.473**	2.29	2.08	2.24	8.23	5.98	27.26
CD	406.587**	597.846**	165.206**	3.38	3.64	6.79	8.99	2.20	75.54
CL	126.751**	7.535**	15.518*	3.69	3.75	0.06	0.39	0.33	15.00
SCL	89.782**	7.073**	14.415*	3.95	4.22	0.06	0.40	0.35	13.78
NSR	43.639**	33.532**	22.937**	5.62	4.41	0.35	0.78	0.42	45.54
YP	0.072**	0.051**	0.101**	2.20	2.29	0.00	0.00	0.00	55.90
1000-GW	27117.704**	18886.593**	14497.502**	3.96	5.85	196.08	459.64	263.56	42.66
Y	10.777**	5.209**	13.851**	3.18	3.10	0.03	0.07	0.04	49.06
Chl.a	129824.022**	10172.615**	15410.709**	3.18	1.76	90.53	111.74	21.22	81.01
Chl.b	32346.700**	2921.739**	4631.382**	3.42	2.03	25.59	30.44	4.85	84.08
Chl.Tot	291552.626**	23961.735**	36622.746**	3.24	1.83	212.59	258.60	46.01	82.21
SPAD	4405.675**	316.994**	822.114**	5.50	5.15	2.14	4.68	2.54	45.75
NDVI.1	0.111*	0.081**	0.178**	24.34	14.96	0.00	0.00	0.00	23.03
NDVI.2	0.023	0.019**	0.076**	16.71	8.22	0.00	0.00	0.00	5.79
NDVI.3	0.008	0.019**	0.046*	14.12	10.4	0.00	0.00	0.00	12.72

Notes: **: significant at α = 1%, *: significant at α = 5%, N: nitrogen, V: variety, N × V: interaction between nitrogen and variety, CV: coefficient of variance, VG: variance of genotypes, VP: variance of phenotypes, H: heritability, PH: plant height, NL: number of leaves, SD: stem diameter, MFA: male flowering age, FFA: female flowering age, ASI: anthesis-silking interval, HA: harvest age, CH: cob height, CW: cob weight, CD: cob diameter, CL: cob length, SCL: seed cob length, NSR: number of seeds per row, YP: yield percentage, 1000-GW: 1000 grain weight, Y: yield, Chl: chlorophyll, SPAD: Soil Plant Analysis Development, NDVI: normalized difference vegetation index.

The interaction showed a very substantial response to the characters and varieties that had mean values of NDVI-UAV, NDVI.1 (40 DAP) (23.03), NDVI.2 (55 DAP) (5.79), and NDVI.3 (70 DAP) (12.72), as shown in Table 1.

3.3 Correlation analysis

Table 2 shows the results of correlation analysis between various phenotypically and destructively collected image-derived characters. The analysis showed significant negative and positive correlations with yield attributes, especially in cob weight characters, namely several leaves (0. 38), male flowering age (−0.23), female flowering age (−0.24), harvesting age (−0.25), cob location (0.25), cob weight (0.76), cob diameter (0.44), cob length (0.23), seeded cob length (0.21), number of seed rows (0.38), yield percentage (0.41), and 1000 seed weight (0.21). Other characteristics did not show significant relationships with yield attributes, indicating that changes in these characteristics did not significantly affect the yield.

3.4 Path analysis

Path analysis showed that cob weight directly affected yield characters with a coefficient of 0.93 (Table 3); this trait also had a considerable indirect effect on other phenotypic characteristics. In addition to cob weight, yield attributes were directly influenced by yield percentage and female flowering age, each with a coefficient. In contrast, the trait with the least direct effect resulted in a cob diameter of −0.01.

3.5 Scatterplot matrix

Figure 2 shows a scatterplot matrix which illustrates the relationship between the variables in the dataset. Each row and column represent a variable and is usually distributed, such as Chl. a (chlorophyll a), Chl. b (chlorophyll b), Chl. Tot (total chlorophyll), SPAD (leaf chlorophyll content indicator), as well as vegetation index variants NDVI.1 (40 DAP), NDVI.2 (55 DAP), and NDVI.3 (70 DAP). The diagonal part displays the variable names, while the rest of the cells show a graph of the relationship between pairs of variables. The patterns seen can be a positive correlation (points form a line rising from the bottom left to the top right), a negative correlation (points form a line falling from the top left to the bottom right), or no relationship (random distribution of points).

3.6 PCA

Based on the PCA (Table 4), four principal components had eigenvalues greater than 1, namely PC1 and PC2, indicating that these components were significant in explaining the data variance, with PC1 explaining 54% of the variance. The eigenvector associated with NDVI.3 at 70 HST for PC1 had a value of −0.08, indicating an inverse relationship between this variable and PC1. However, PC2 showed variance values of 0.18% and 0.72%. This means that when NDVI values increase, PC1 values decrease, and vice versa. NDVI at 70 DAP plays an essential role in PC1, and PC1 can be used to weigh the selection index.

4 Discussion

NDVI analysis shows that the nitrogen and variety interaction had good vegetation index values in the 55 DAP observation phase. The validation test results show the potential of imagery with this model to estimate vegetation greenness, especially by using vegetation index values with a strong relationship with field measurements [24,31]. According to the studies of García-Martínez et al. and Padjung et al. [6,14], using UAVs with ArcGIS software provides complete and accurate data information. Digital image data from the light range obtained from uncrewed aircraft can be used to quickly assess and record the leaf chlorophyll content and N content in corn plant leaves. Using UAVs and multispectral cameras, data capture can produce high-resolution NDVI readings [7,32]. NDVI is highly proposed because light absorption and reflectance in leaves have been measured using a technological approach from satellites. NDVI data provide a strong approximation when measuring the leaf chlorophyll content and nitrogen concentration during the growing season.

The application of multivariate analysis techniques, such as Pearson correlation, path analysis, and PCA, is effective assessment packages for selection [33–35]. The correlation results show that cob weight is the selected character, with the yield attribute showing a coefficient value of around 0.76. According to the study of Mustafa et al. [36], if the correlation value is closer to +1, then the increase in one trait will follow the increase in the other trait, and closer to −1 indicates that the increase in one trait

Table 2: Correlation analysis of all analyzed traits

	PH	NL	SD	MFA	FFA	ASI	HA	CH	CW	CD	CL	SCL	NSR	YP	1000-GW	Y
PH	1.00	−0.03tn	0.21*	0.03tn	−0.01tn	−0.21*	−0.02tn	0.23*	−0.27**	0.31**	0.06tn	0.01tn	0.07tn	0.28**	0.26**	−0.08tn
NL		1.00	0.07tn	0.03tn	0.02tn	−0.09tn	0.01tn	0.18tn	0.00tn	0.16tn	0.23*	0.16tn	0.32**	0.21*	0.24*	0.14tn
SD			1.00	−0.29**	−0.35**	−0.43**	−0.35**	0.24*	0.27**	0.54**	0.48**	0.44**	0.44**	0.17tn	0.48**	0.38**
MFA				1.00	0.99**	0.11tn	0.98**	−0.03tn	−0.08tn	−0.51**	−0.27**	−0.22*	−0.2*	−0.26**	0.01tn	−0.23*
FFA					1.00	0.28**	0.99**	−0.04tn	−0.09tn	−0.54**	−0.34**	−0.3**	−0.24*	−0.26**	−0.05tn	−0.24*
ASI						1.00	0.28**	−0.05tn	−0.09tn	−0.29**	−0.48**	−0.48**	−0.29**	−0.08tn	−0.4**	−0.14tn
HA							1.00	−0.04tn	−0.1tn	−0.54**	−0.36**	−0.31**	−0.25*	−0.25*	−0.06tn	−0.25*
CH								1.00	0.15tn	0.29**	0.05tn	0.00tn	0.44**	0.16tn	0.04tn	0.25**
CW									1.00	0.19*	0.21*	0.21*	0.24*	−0.26**	0.12tn	0.76**
CD										1.00	0.41**	0.35**	0.52**	0.40**	0.43**	0.44**
CL											1.00	0.91**	0.47**	0.03tn	0.52**	0.23*
SCL												1.00	0.45**	−0.01tn	0.45**	0.21*
NSR													1.00	0.21*	0.30**	0.38**
YP														1.00	0.12tn	0.41**
1000-GW															1.00	0.21*
Y																1.00

Notes: **: significant at α = 1%, *: significant at α = 5%, PH: plant height, NL: number of leaves, SD: stem diameter, MFA: male flowering age, FFA: female flowering age, ASI: anthesis-silking interval, HA: harvest age, CH: cob height, CW: cob weight, CD: cob diameter, CL: cob length, SCL: seed cob length, NSR: number of seeds per row, YP: yield percentage, 1000-GW: 1000 grain weight, Y: yield.

Table 3: Path analysis of traits that remained positive toward results

Character	Direct effect	Indirect effect												Residual
		SD	MFA	FFA	HA	CH	CW	CD	CL	SCL	NSR	YP	1000-GW	
SD	0.02		0.01	−0.12	0.10	0.00	0.25	−0.01	0.02	−0.01	0.01	0.11	0.00	0.13
MFA	−0.04	−0.01		0.33	−0.28	0.00	−0.07	0.01	−0.01	0.00	0.00	−0.17	0.00	0.13
FFA	0.33	−0.01	−0.03		−0.28	0.00	−0.08	0.01	−0.01	0.01	0.00	−0.17	0.00	0.13
HA	−0.28	−0.01	−0.03	0.33		0.00	−0.09	0.01	−0.01	0.01	0.00	−0.16	0.00	0.13
CH	0.00	0.01	0.00	−0.01	0.01		0.14	0.00	0.00	0.00	0.01	0.11	0.00	0.13
CW	0.93	0.01	0.00	−0.03	0.03	0.00		0.00	0.01	0.00	0.00	−0.17	0.00	0.13
CD	−0.01	0.01	0.02	−0.18	0.15	0.00	0.18		0.01	−0.01	0.01	0.26	0.00	0.13
CL	0.04	0.01	0.01	−0.11	0.10	0.00	0.20	−0.01		−0.02	0.01	0.02	0.00	0.13
SCL	−0.02	0.01	0.01	−0.10	0.09	0.00	0.20	0.00	0.03		0.01	−0.01	0.00	0.13
NSR	0.02	0.01	0.01	−0.08	0.07	0.00	0.22	−0.01	0.02	−0.01		0.14	0.00	0.13
YP	0.66	0.00	0.01	−0.09	0.07	0.00	−0.24	−0.01	0.00	0.00	0.00		0.00	0.13
1000-GW	0.00	0.01	0.00	−0.02	0.02	0.00	0.11	−0.01	0.02	−0.01	0.01	0.08		0.13

Notes: SD: stem diameter, MFA: male flowering age, FFA: female flowering age, HA: harvest age, CH: cob height, CW: cob weight, CD: cob diameter, CL: cob length, SCL: seed cob length, NSR: number of seeds per row, YP: yield percentage, 1000-GW: 1000 grain weight.

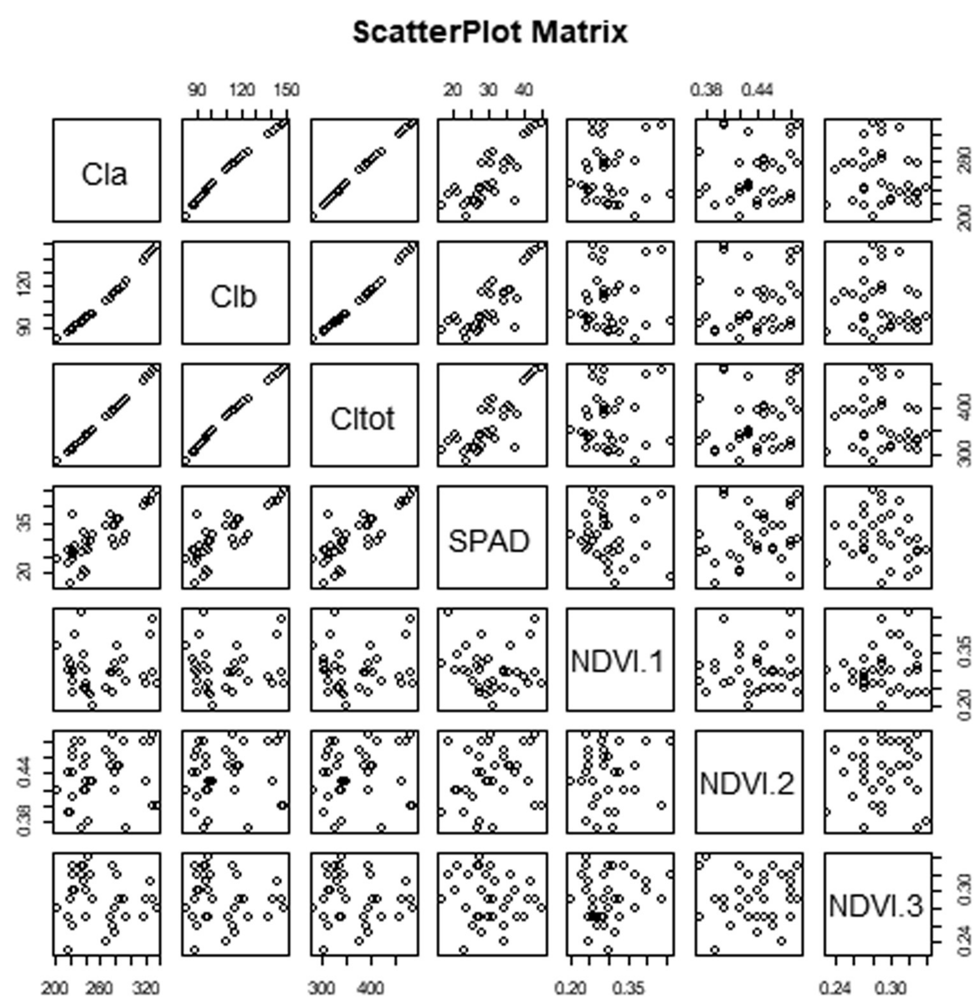

Figure 2: Relationship between characters in the matrix scatterplot.

Table 4: PCA of image-based maize physiological characters

Character	PC1	PC2	PC3	PC4	PC5
Chl.a	0.50	0.01	−0.10	0.05	0.28
Chl.b	0.51	0.02	−0.12	0.03	0.22
Chl.Tot	0.51	0.01	−0.11	0.04	0.26
SPAD	0.46	−0.10	0.14	0.10	−0.87
NDVI.1	0.02	0.66	−0.53	−0.49	−0.21
NDVI.2	0.13	0.49	0.82	−0.26	0.11
NDVI.3	−0.08	0.56	−0.06	0.82	−0.02
Standard deviation	1.95	1.11	0.93	0.93	0.46
Proportion of variance	0.54	0.18	0.12	0.12	0.03
Cumulative proportion	0.54	0.72	0.85	0.97	1.00
Eigen values	3.81	1.24	0.87	0.86	0.21

Notes: Chl: chlorophyll, SPAD: Soil Plant Analysis Development, NDVI: normalized difference vegetation index, and PC: principal component.

will decrease the other trait. This suggests that there is a proportion of each character's value that is indicative of the yield attribute.

Based on the results of correlation analysis, the number of leaves, male flowering age, female flowering age, harvesting age, cob location, cob weight, cob diameter, cob length, seed cob length, number of seed rows, yield percentage, and 1,000 seed weight have a significant influence on the yield, so these characters can be used as a benchmark or as a consideration in determining nitrogen fertilizer packages, varieties, and the interaction of nitrogen fertilizer packages with varieties in this study. According to research on hybrid corn [37,38], one of the characteristics that correlates very significantly with yield is cob weight. This proves that cob weight influences the yield, where the grain yield increases considerably according to the increase in cob weight. The increase in cob weight in corn plants will align with the yield obtained. This aligns with the research of Fromme et al. [39], which states that cob weight affects corn production because the more significant the cob weight is, the greater the corn production. Therefore, quality seeds and high seed productivity can be produced by selecting plant height, cob height, diameter, number of seed rows, 1,000 seed weight, cob length, and cob weight.

The correlation matrix table between observation parameters where SPAD, chlorophyll, and NDVI value characters significantly correlated with productivity [12,15,40]. The more active the photosynthesis process is, the higher the NDVI value, and the lower the greenness of the plant, the lower the NDVI value. The relationship between the NDVI and the maize growth phase is related to the variation of NDVI values in each growth phase.

Based on the observations, the 40 and 55 DAP intervals show a significant effect, with the results measured at 40 DAP and 55 DAP showing substantial differences in plant growth and yield. According to studies of Panek and Gozdowski and Xue and Su [32,41], their research explained that moderate vegetation age, plant stand density, and plant canopy density generally provide high ratio values in vegetation index values. In this study, it is analogous that stand density also affects the crown density, so the analysis results show a strong relationship. The denser the vegetation stands, the greater the crown density, which will affect the vegetation index value. The taller the corn plant and the older the plant, the denser the leaf canopy. Growth and changes in vegetation canopy cover that are relatively thicker and denser significantly affect the pixel value of aerial imagery, so that the chlorophyll and nitrogen vegetation index values are higher.

Combining these two characteristics with yield is optimal for developing a selection index. However, the selection index should be considered based on the priority value or variance of the characteristics. This priority can be done with used path analysis and PCA, which indicate the genotype selection index [16,33]. However, the eigenvalues of selection characteristics can be weighted with a positive sign because the negative sign is limited to the direction of variance and not to the absolute value [35]. The effectiveness of the three indices is determined using heritability analysis of the selection indices, which indicates the efficacy of genetically weighted combinations [1,42]. Combining some secondary characters with yield characters can increase the genetic potential of the main character, such as the yield, which increases the effectiveness of selection compared to using the yield alone. [30] We reported the same efficacy in wheat selection [29] in rice under salinity stress. However, the in-depth analysis still included characters with significant genetic correlations.

5 Conclusions

In conclusion, traits related to cob weight, flowering time, and yield percentage significantly improve the maize yield, with high heritability values making them selection criteria. Vegetation indices, such as NDVI at 70 DAP, play a significant role in PC1, and PC1 can be used to weigh selection indices. These findings provide valuable insights for improving maize production through targeted breeding strategies and field trials that can determine the best maize cultivation technologies that farmers can use.

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